**REGULAR QUESTIONS – 1**

**Object Detection Questions**

1. Explain the role of feature pyramids in object detection models like RetinaNet.

2. What is the significance of data augmentation in training object detection models?

3. How does a Region Proposal Network (RPN) function in Faster R-CNN?

4. What metrics would you use to evaluate an object detection model's performance?

5. How would you optimize an object detection model for real-time performance on edge devices?

**Object Detection Questions**

**1. Role of feature pyramids in object detection models like RetinaNet:**  
Feature pyramids are crucial in handling objects of varying scales. They allow the model to detect small, medium, and large objects by creating feature maps at multiple scales. RetinaNet uses a Feature Pyramid Network (FPN) to extract features at different resolution levels from a backbone CNN. These multi-scale features are fused with lateral connections, ensuring both high-level semantic information and fine-grained details are preserved across scales.

**2. Significance of data augmentation in training object detection models:**  
Data augmentation increases the diversity of training data by applying transformations like rotation, flipping, cropping, scaling, and color adjustments. This helps the model generalize better, reduces overfitting, and improves robustness to variations in real-world data. For object detection, augmentations like random cropping, brightness changes, and random scaling ensure the model learns to detect objects under different conditions.

**3. How a Region Proposal Network (RPN) functions in Faster R-CNN:**  
RPN is a module that generates object proposals (regions likely to contain objects) in an image. It uses sliding windows on feature maps produced by a backbone network. For each window, RPN predicts:

* Objectness scores (whether a region contains an object or not).
* Bounding box coordinates for potential objects.  
  Anchor boxes at multiple scales and aspect ratios are used for proposal generation. Non-Maximum Suppression (NMS) is applied to filter overlapping proposals.

**4. Metrics to evaluate an object detection model's performance:**

* **Mean Average Precision (mAP):** Evaluates precision-recall tradeoff across classes and IoU thresholds.
* **Intersection over Union (IoU):** Measures the overlap between predicted and ground truth bounding boxes.
* **Precision and Recall:** Assess the trade-off between false positives and false negatives.
* **Frames Per Second (FPS):** For real-time performance evaluation.

**5. Optimizing an object detection model for real-time performance on edge devices:**

* Use lightweight architectures like MobileNet or YOLO.
* Quantize the model (e.g., 8-bit integer precision).
* Use model pruning to remove unnecessary parameters.
* Apply hardware acceleration (e.g., TensorRT for NVIDIA devices).
* Reduce input resolution while maintaining acceptable accuracy